



Adaptive contour-based statistical background subtraction method for moving target detection in infrared video sequences



Aparna Akula^{a,b,*}, Nidhi Khanna^c, Ripul Ghosh^{a,b}, Satish Kumar^b, Amitava Das^b, H.K. Sardana^{a,b}

^aAcademy of Scientific and Innovative Research (AcSIR), New Delhi 110001, India

^bComputational Instrumentation, Central Scientific Instruments Organisation (CSIR-CSIO), Chandigarh 160030, India

^cDepartment of Computer Science and Engineering, Chitkara University, Himachal Pradesh, India

HIGHLIGHTS

- Adaptive statistical background subtraction model.
- Robust detection of non-uniform and variable thermal profile targets like vehicles.
- State of the art performance on a diverse dataset of thermal infrared sequences.
- High detection rate with low false alarms.

ARTICLE INFO

Article history:

Received 26 August 2013

Available online 30 December 2013

Keywords:

Infrared

Statistical background subtraction

Contour saliency map

Silhouettes

ABSTRACT

A robust contour-based statistical background subtraction method for detection of non-uniform thermal targets in infrared imagery is presented. The foremost step of the method comprises of generation of background frame using statistical information of an initial set of frames not containing any targets. The generated background frame is made adaptive by continuously updating the background using the motion information of the scene. The background subtraction method followed by a clutter rejection stage ensure the detection of foreground objects. The next step comprises of detection of contours and distinguishing the target boundaries from the noisy background. This is achieved by using the Canny edge detector that extracts the contours followed by a *k*-means clustering approach to differentiate the object contour from the background contours. The post processing step comprises of morphological edge linking approach to close any broken contours and finally flood fill is performed to generate the silhouettes of moving targets. This method is validated on infrared video data consisting of a variety of moving targets. Experimental results demonstrate a high detection rate with minimal false alarms establishing the robustness of the proposed method.

© 2013 Elsevier B.V. All rights reserved.

1. Introduction

Moving target detection is an active research area in Computer Vision whose territory spans across various applications like human identification, robotics, surveillance and perimeter monitoring systems [1]. Target detection refers to the task of determining whether or not an object is present in the scene, and if present, identifying its location and size, and extracting it from the background [2]. The criticality of the applications demand persistent and ubiquitous detection of targets. Focusing on robustness, omnipresence and 24×7 applicability, the long wave infrared region of Electromagnetic spectrum is explored. Thermal infrared cameras detect the amount of thermal energy that is

emitted by all objects with temperature above absolute zero. As long as there is some difference in the thermal properties of foreground and background, the subsequent region appears in contrast from the background, making thermal cameras capable for detection in both day and night time [2]. By using thermal imaging, problems like soft shadows, sudden illumination changes, lack of visibility caused due to harsh environmental conditions and night time can be avoided. However, thermal imaging imposes certain challenges like low signal-to-noise, non-repeatability of target signature, competing background clutter, lack of a priori information, and weather induced artefacts [3]. As this paper describes target detection for vehicles, the major challenge is that the thermal signature of vehicles shows a high degree of variability. It is observed that the thermal signature of the same vehicle is different at different time of the day. Moreover thermal profile of vehicles varies from one part of vehicle to another. The wheels of vehicles have different thermal profile when compared to the metal body. The

* Corresponding author at: Computational Instrumentation, Central Scientific Instruments Organisation (CSIR-CSIO), Chandigarh 160030, India. Tel.: +91 172 2637994.

E-mail address: aparna.akula@csio.res.in (A. Akula).

area near the engine is hotter than doors and the windscreen also has a different thermal profile. It is also observed that the thermal profile of natural objects like humans, trees, etc. is uniform as compared to artificial objects. Another challenge of infrared images is the lack of prominent edge and boundary information in thermal imagery, making detection and segmentation of the object from the image a very complex task.

Addressing these challenges an adaptive contour-based statistical background subtraction technique is proposed for detection of moving targets in infrared images. The method is designed to handle the challenges imposed for detection of moving vehicles, however it is also equally capable of detecting humans in thermal imagery. Moreover, the proposed method does not depend on any a priori information of shape or motion for detection. The proposed method has been tested on six challenging infrared videos from the available “CSIR-CSIO Moving Object Thermal Dataset” [3].

2. Related work

After the image acquisition, the first step in recognition applications is to partition objects of interest generally the foreground from the background, and largely the objects of interest are usually in motion. Hence, motion plays an important role in target detection. Various shapes, different orientation of motions, non-rigid structure occlusions, halos and sudden illumination changes pose significant challenges in the extraction of foreground objects from the background of an image. There exist several approaches in the literature to detect targets and tackle the issues discussed above. These can be classified into two broad categories training based approaches and others which do not require any training.

Some of the detection approaches that require training are examined using wavelet template [4] and binary template matching [5]. Color and texture invariant wavelet template, followed by Support Vector Machine (SVM) classifiers is proposed in [4]. In [6] a shape based hierarchical approach using color and gradient information based on pixel, region and frame level information and coarse-to-fine edge matching has been discussed which is robust to shifting of static background objects, illumination changes, and initialization of background model. An approach for detecting objects based on motion pattern, appearance and trained using AdaBoost to take advantage of both motion and appearance information is proposed in [7]. A two-step detection/tracking method is proposed in [8] where the detection phase is performed by SVM and the tracking phase is a combination of Kalman filter prediction and mean shift tracking. A novel approach for detecting and tracking objects using frame level partitioning and finding correlation is examined in [9] which do not require training. An approach of object detection that does not require large training sets, and also provides the silhouettes of the detected objects is background-subtraction. Here “foreground” regions are identified by subtracting the input image from a background model. To achieve this, an accurate and adaptive background model is often desirable. Using the basic statistical approaches, a distribution for each pixel is modelled as a single Gaussian [10,11], and then any new pixel that does not belong to the distribution is stated as a foreground pixel. A Mixture of Gaussians was proposed in [12] to model the complex background processes of each pixel in a better way. The Mixture of Gaussians approach was also examined in [13]. Other statistical approaches based on standard background-subtraction technique and gradient information are deliberated in [14–16].

Researcher's have proposed various methods of generating background models. In [17], to obtain the distribution of pixel intensities for background modelling, kernel density estimator was proposed. A variable-bandwidth kernel density estimator was proposed in [18]. The analysis of input video based on time

is another technique used to create dynamic background models. Kalman filters for adaptive background were used in [19], and an auto-regressive model was used in [20]. Background subtraction model for dynamic scenes was proposed in [21]. An adaptive background model for dynamic scenes using kernel density [22] was also examined. Wiener filters were employed in three stages (pixel, region and frame) in the Wallflower approach [23]. A background subtraction technique for moving cameras is examined in [24].

The advantage of employing background-subtraction for object detection is that the regions in motion are directly obtained. However, these classes of methods have two debilitating drawbacks. First, these methods require the camera to be stationary, so that reliable background models can be built. This greatly limits the applicability of such methods. Secondly, these methods by themselves do not discriminate between different object classes, and all foreground objects in the scene are detected. However, in applications like perimeter monitoring, virtual fencing where the background is constant, computationally efficient background subtraction approaches are popular.

The proposed approach is inspired from the contour based statistical background subtraction method discussed in [16], which is used for human detection. It uses the “halo effect” produced by common ferroelectric BST sensors based infrared detector that appears around very hot or cold objects present in the scene. The work has been extended for thermal video sequences of vehicles captured using micro bolometer type infrared detector. The absence of halo effect which acted as an important feature to detect objects in case of [16] is not present in microbolometer type IR detector and the complex non-uniform thermal signature of vehicles pose great challenges and the method proposed in [16] when applied directly fails to achieve accurate results. To handle these issues, several modifications and extensions are proposed which are discussed in the paper.

3. Proposed method

The proposed approach shown in Fig. 1 can be broadly divided into three stages, namely-Foreground Object Detection based on Statistical Background Subtraction, Contour Detection uses Contour Saliency Map and Silhouette Generation.

3.1. Foreground object detection (FOD)

The first step of FOD is to generate a Statistical Background Model, which can represent the background accurately. This demands that the input thermal video contains an adequate number of initial frames without objects to generate a background model. To construct a statistical background model, firstly a reference background is generated from an initial set of N frames by taking the pixel wise median of each frame, which is named as median Image (I_{med}). The statistical background model for each pixel of the input set of N frames is formed by calculating the weighted mean (μ) and variance (σ^2) as described in Eqs. (1) and (2).

$$\mu(x, y) = \frac{\sum_{i=1}^N W_i(x, y) \cdot I_i(x, y)}{\sum_{i=1}^N W_i(x, y)} \quad (1)$$

$$\sigma^2(x, y) = \frac{\sum_{i=1}^N W_i(x, y) \cdot (I_i(x, y) - \mu(x, y))^2}{\sum_{i=1}^N W_i(x, y)} \quad (2)$$

where $I_i(x, y)$ is the intensity of pixel located at (x, y) in the i th frame, the weights $W_i(x, y)$ for each pixel location (calculated using Eq. (3)) are used to minimize the effect of outliers.

$$W_i(x, y) = \exp\left(\frac{(I_i(x, y) - I_{med}(x, y))^2}{-2SD^2}\right) \quad (3)$$

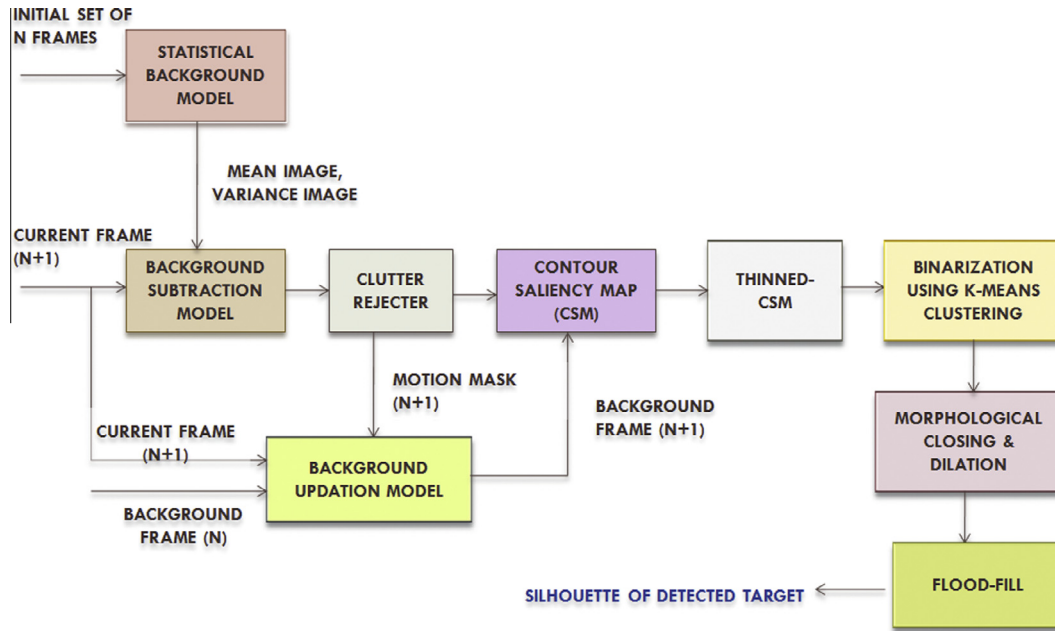


Fig. 1. Block diagram of the proposed adaptive contour-based statistical background subtraction method.

After experimental evaluation, the value of SD is taken to be 5. Fig. 2 shows the generated median, weighted mean and weighted variance images of a background frame for vehicle sequence (“Innova”). After generating the mean/variance background model, the foreground object(s) for the given input frame (I) is obtained using the squared Mahalanobis distance, where any pixel greater than the threshold (distance) is taken as a foreground pixel as described in Eq. (4).

$$F(x, y) = \begin{cases} 1, & \frac{(I(x, y) - \mu(x, y))^2}{\sigma(x, y)^2} > T^2 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

In this work, the value of T is set as $T^2 = 81$ after experimental evaluation.

A connected component algorithm is used, in which all the components that are connected to each other is computed and labelled as one entity. To segregate the obtained foreground objects from the background pixels basic a priori information of area and aspect ratio are used and clutter is discarded. Fig. 3 shows the output of the connected component algorithm and output after clutter rejection stage.

3.2. Contour detection

This stage involves extraction of the contours of the target from the detected foreground object. For detecting contours, the gradient information of the input frame and its corresponding background is used. Instead of simple input-background gradient

difference magnitude, a contour saliency map (CSM) is computed to suppress large non-object gradient magnitudes and large non-object gradient difference magnitude of input and background. A CSM is computed by calculating the pixel-wise minimum of the normalized input gradient magnitudes and the normalized input-background gradient-difference magnitudes as described in Eq. (5).

$$CSM = \min \left(\frac{\| \langle I_x, I_y \rangle \|}{Max}, \frac{\| \langle (I_x - B_x), (I_y - B_y) \rangle \|}{Max} \right) \quad (5)$$

where I_x and I_y are the gradient of input image in the horizontal and vertical directions respectively, B_x and B_y are the gradient of input image in the horizontal and vertical directions respectively, the normalization factor Max is the respective maximum magnitudes of input gradients and the input-background gradient-difference of the foreground object region. The value of pixels in the CSM is in the range of $[0, 1]$, with larger values indicating stronger confidence that a pixel belongs to the object boundary. The value of each pixel in CSM represents the confidence of that pixel belonging to the boundary of a foreground object.

To ensure that the background aptly corresponds to the current frame, an adaptive background updation model is used to generate background frame corresponding to each input frame. In this work, an adaptive background frame is generated using a motion based background updation process to capture the naturally occurring temperature variations. Background of the current frame $B_{n+1}(x, y)$ is generated using the information of the motion mask obtained from clutter rejecter stage, current frame $I_{n+1}(x, y)$ and the previous background $B_n(x, y)$. Any pixel which is in motion is treated as



Fig. 2. (a) The median image (I_{med}), (b) weighted mean image (μ), (c) weighted variance image (σ^2).



Fig. 3. (a) Output of the connected component algorithm, (b) Output after clutter rejection stage.

foreground pixel and is assigned the value of previous background and pixel that is not in motion is updated using the information from the previous background and current frame as described in Eq. (6).

$$B_{n+1}(x, y) = \begin{cases} \alpha B_n(x, y) + (1 - \alpha)I_{n+1}(x, y), & \text{if } (x, y) \text{ is non-moving} \\ B_n(x, y), & \text{if } (x, y) \text{ is moving} \end{cases} \quad (6)$$

where α is the weight parameter indicating the significance of previous background while updating the background.

To produce thin contours, called tCSM, a non maximum suppression of edges is performed using the canny operator. The next step is to convert the tCSM into a binarized tCSM image to choose the most significant contours. To achieve this, a single threshold value is required that selects the majority of the object's contours and at the same time capable of eliminating the background noise contours. To select the threshold value, k-means clustering with 2 clusters, representing targets and background are formed, the lower cluster is discarded as background by setting the pixel value in this cluster to zero and the pixels corresponding to the higher cluster are taken as foreground pixels by setting the pixel to one. Fig. 4 shows the output obtained after CSM, tCSM and binarized tCSM stages respectively.

3.3. Silhouette generation

The final step of target detection involves generation of target silhouettes from the contour image. The binarized contours obtained are mostly broken; therefore flood fill operation cannot be directly applied to obtain the silhouettes. In order to get the silhouettes of the detected target there is a need to close and complete the broken contours. Morphological dilation using diamond structuring element followed by a morphological closing using disk structuring element is applied to complete and close the broken binarized contours. The closed contours are finally flood filled to get the silhouettes of the detected target. Fig. 5 shows an input frame containing target and the corresponding silhouette of the target generated by the proposed method.

4. Experimental data–‘CSIR-CSIO Moving Object Thermal Dataset’

The proposed approach is tested with six challenging infrared video sequences comprising of both vehicle and human sequences, four sequences consisting of different type of vehicles and two sequences of humans. These sequences are part of ‘CSIR-CSIO Moving Object Thermal Dataset’ consisting a total of 18 thermal video sequences of 640×480 pixel resolution captured using a micro bolometer type thermal image, at two temperature and weather conditions, i.e. around 11:00 am on a hot sunny day and 4:00 pm on a cool and light shower's day. However, in this work only six

infrared video sequences out of 18 were analysed in this work as the proposed method demands significant number of background frames for generation of the ‘Statistical Background Model’ which are not available in other sequences. The total number of frames, maximum number of background frames in the sequence, the number of background frames used in the proposed method to generate the Statistical Background Model are listed in Table 1.

5. Results and discussion

To evaluate the performance of the proposed method, we compared it with the popular Mixture of Gaussians (GMM) [12] and Pseudo Wigner distribution and Rényi entropy based background subtraction (PWD-RE) [3] methods. The optimized GMM implementation provided in the MATLAB® Computer Vision System toolbox is used in this work for comparative analysis. As can be seen from Fig. 6 in the GMM approach, a single region is split into multiple parts thereby depicting it as multiple objects. Moreover it has a number of false detections in the ‘Innova’ sequence due to variation in atmospheric conditions and inherent thermal noise. It is evident from the qualitative comparison shown in Fig. 6 that the proposed method outperforms the GMM and it is able to extract the entire region containing the target as a single entity with no false detections; this is due to the use of contour saliency information along with the conventional background subtraction. In case of the PWD-RE method, we were able to detect the objects without any false detection. However, it does not provide much detail about the shape and detects a much larger area than the actual object region, which can be seen in Fig. 6. This is because the PWD-RE approach focuses on high detection with low false alarm and not the exact shape or boundary of the object. On the contrary the proposed method inherently emphasises on the shape aspect by using the contour information, thereby providing a better silhouette of the object.

To demonstrate the performance of the proposed method; evaluation metrics, Sensitivity, PPV and F-measure are used. Sensitivity is an indicator of detection rate and PPV is an indicator of false alarms. A high Sensitivity value corresponds to a high detection rate, and a high PPV corresponds to a low false alarms. F-measure, the harmonic mean of Sensitivity and PPV is also computed to depict the overall performance of the method. Closer the F-measure value to unity better is the performance of the detection method in terms of both detection rate and false alarms.

The development environment of the proposed method is MATLAB R2011a on an Intel Xeon CPU X5660 at 2.80 and 2.79 GHz (two processors) with 12 GB RAM. It is to be noted that the current implementation is not optimized for computational efficiency, this can be achieved by parallel processing and vectorization of the implementation. However, it was observed that even the non-optimized version of the proposed method is computationally efficient with an average processing time of 0.6766sec/frame.

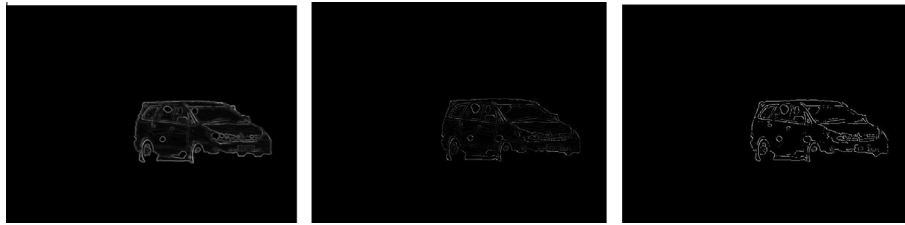


Fig. 4. (a) Output of CSM, (b) Output of tCSM, (c) Output of binarized tCSM.



Fig. 5. (a) Input Frame, (b) corresponding silhouette of the target generated by the proposed method.

Table 1

Description of the “CSIR-CSIO Moving Object Thermal Dataset”.

Seq. No.	Infrared video name	Total frames	No. of background (BG) frames in the video sequence	No. of BG frames used for the statistical BG model
1	Ambassador_Far_Bird	185	60	30
2	Auto_Near	126	53	35
3	Bike_Complex_Background	136	39	26
4	Innova	137	29	21
5	Person_Sack_Walking_Morning	142	1	1
6	Person_Walking_Morning	208	14	12

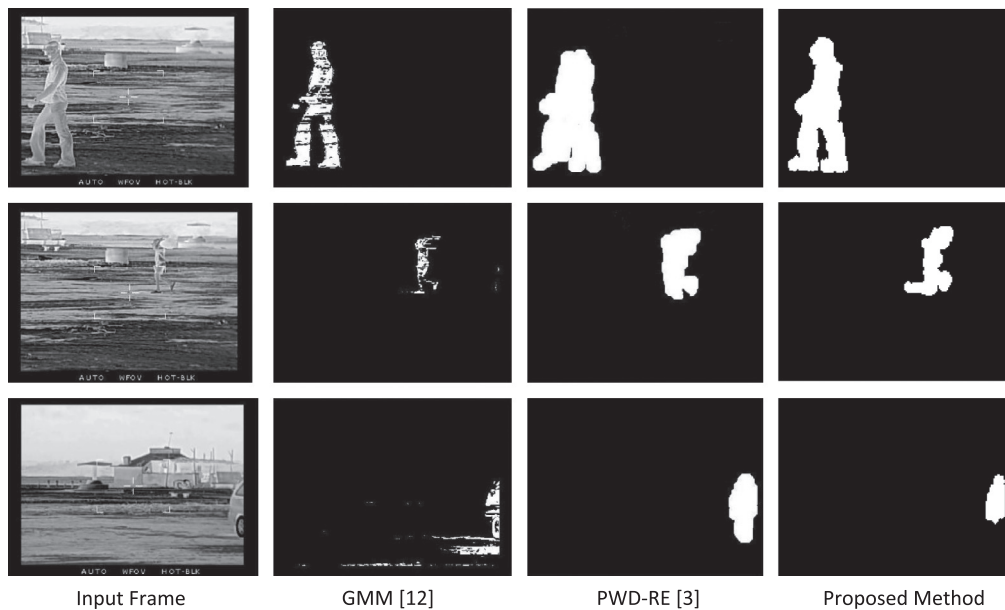


Fig. 6. Qualitative comparison of detection results of GMM, PWD-RE and the proposed approach across different video sequences (Sequence No. 4–6, bottom-up).

It can be observed from Table 2 that the proposed method has 100% detection rate and low false alarm rate. For *Ambassador_far_bird* sequence, both the two objects in motion, car and bird are detected considerably well despite of very less vehicle to background contrast. In *Auto_near* and *Innova* sequences in spite of

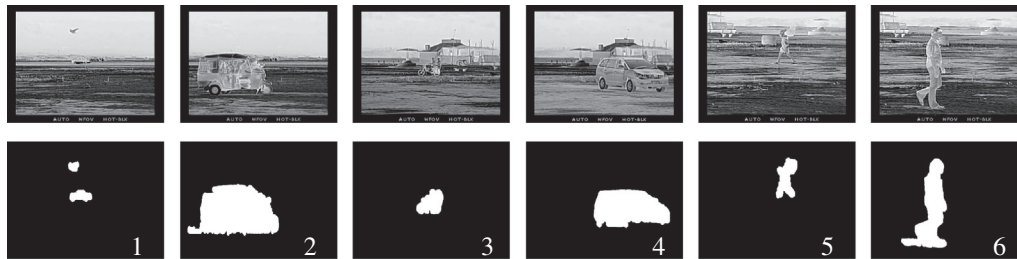
non-uniform intensity profile of the vehicle and partial occlusion of auto, the algorithm is able to clearly detect and generate the silhouettes of the vehicle. It is also efficient in detecting small targets in a complex background, which was observed in the *Bike_complex_background* sequence. The proposed method has

Table 2

Detection results for the thermal video sequences.

Thermal Video Sequence	GT	TP	FP	$S = TP/GT$	$PPV = TP/(TP + FP)$	F -measure	Comp. Time (s/frame)
Ambassador_far_bird	106	106	0	1	1	1	0.5197
Auto_near	40	40	0	1	1	1	0.7576
Bike_complex_background	81	81	2	1	0.9759	0.9878	0.6532
Innova	88	88	0	1	1	1	0.6697
Person_sack_walking_morning	126	126	1	1	0.9921	0.9960	0.6840
Person_walking_morning	113	113	15	1	0.8928	0.9433	0.7753
Total	645	645	18	1	0.9768	0.9895	0.6766

(Key: GT: Ground Truth, TP: True Positive, FP: False Positive, S: Sensitivity, PPV: Positive Predictive Value).

**Fig. 7.** Output of the six infrared video sequences (Sequence 1–6 left–right), Input frame (top row) and the corresponding output target silhouette (below row).

demonstrated accurate detection for pedestrian sequences as well. Few false positives occurred in *Person_walking_morning* sequence, because of the thermal profile generated by the shadow of the person. The overall performance of the proposed method is high with an average sensitivity of 1 and average F -measure of 0.9895, which is fairly high for the chosen dataset containing a variety of targets. Fig. 7 shows the output of the proposed method for randomly chosen input frame of all the six sequences.

6. Conclusion

The proposed algorithm is tested to handle a variety of situations like complex background, different environmental conditions and varying target to sensor distance. It is evident from the results that the proposed method is able to solve the problems posed by thermal imagery. Moreover the proposed method can effectively detect both uniform (humans) as well as non-uniform (vehicles) moving targets. High values of the F -measure obtained is an indicative of the robustness of the proposed method for target detection purposes. The performance of the proposed method can be further enhanced by incorporating efficient edge linking technique for accurate retrieval of the object boundary and also a more robust statistical background model considering higher order statistics. In conclusion, the authors propose a robust adaptive contour-based statistical background subtraction technique with a high detection probability and a low false-alarm probability for moving target detection in infrared image sequences.

References

- [1] Aparna Akula, Ripul Ghosh, H.K. Sardana, in: AIP Conf. Proc. 1391, Optics: Phenomena, Materials, Devices, And Characterization: OPTICS 2011: International Conference on Light, pp. 333–335.
- [2] Vinay Sharma, Simultaneous Object detection and Segmentation using Top-Down and Bottom-up processing, B.E. (Honors), The Ohio State University, Columbus, United States of America, 2008.
- [3] A. Akula, R. Ghosh, S. Kumar, H. Sardana, Moving target detection in thermal infrared imagery using spatiotemporal information, *J. Opt. Soc. Am. A* 30 (2013) 1492–1501.
- [4] M. Oren, C. Papageorgiou, P. Sinha, E. Osuna, T. Poggio, "Pedestrian detection using wavelet templates", in: Proceedings, 1997 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 17–19 June 1997, pp. 193–199.
- [5] Dong-San Jun, Sun-Gu Sun, HyunWook Park, "Automatic target detection using binary template matching", *Opt. Eng.* 44, March 23, 2005 036401.
- [6] Omar Javed, Khurram Shafique, Mubarak Shah, A hierarchical approach to robust background subtraction using color and gradient information, in: *workshop motion video computing, IEEE (2002)* 22–27.
- [7] P. Viola, M.J. Jones, D. Snow, Detecting pedestrians using patterns of motion and appearance, in: Proceedings of Ninth IEEE International Conference on Computer Vision 2003, vol. 2, 2003, pp. 734–741.
- [8] Fengliang Xu, Xia Liu, K. Fujimura, Pedestrian detection and tracking with night vision, *Intell. Transport. Syst. IEEE Trans.* 6 (1) (2005) 63–71.
- [9] Manoj S. Nagmode, Mrs. Madhuri A. Joshi, Ashok M. Sapkal, A Novel approach to Detect and Track Moving Object using Partitioning and Normalized Cross Correlation. In *ICGST-GVIP Journal*, ISSN: vol. 9 (4) 2009 pp. 1687–398X.
- [10] C.Wren, A. Azarbayejani, T. Darrell, A. Pentland, Pfunder: real-time tracking of the human body, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 19(7) 1997 pp. 780–785.
- [11] I.Haritaoglu, D. Harwood, and L. Davis. W4: Who? When? Where? What? A real time system for detecting and tracking people, in: *Proc. Int. Conf. Auto. Face and Gesture Recog.*, 1998, pp. 222–227.
- [12] C. Stauffer, W.E.L. Grimson, Adaptive background mixture models for real-time tracking, *Proc. Comput. Vision Pattern Recognit. IEEE (1999)* 246–252.
- [13] M. Harville. A framework for high-level feedback to adaptive, per-pixel, mixture-of-gaussian background models. in: *Proc. European Conference on Computer Vision*, 2002, pp. 543–560.
- [14] J.W. Davis, V. Sharma, "Robust Background-Subtraction for Person Detection in Thermal Imagery", Conference on Computer Vision and Pattern Recognition Workshop, CVPRW '04, 2004, 27–02 June, 2004, pp. 128.
- [15] J.W. James Davis, V. Sharma, "Robust detection of people in thermal imagery", in: Proceedings of the 17th International Conference on Pattern Recognition, ICPR 2004, vol. 4, 23–26 Aug. 2004, pp. 713–716.
- [16] J. Davis, V. Sharma, Background-subtraction in thermal imagery using contour saliency, *Int. J. Comput. Vision* 71 (2) (2007) 161–181.
- [17] A. Elgammal, D. Harwood, L. Davis. Non-parametric model for background subtraction. in: *Proc. European Conference on Computer Vision*, 2004, pp. 751767.
- [18] A. Mittal, N. Paragios, Motion-based background subtraction using adaptive kernel density estimation, *Proc. Comput. Vision Pattern Recognit. (2004)* 302–309.
- [19] Jing Zhong, S. Sclaroff, "Segmenting foreground objects from a dynamic textured background via a robust Kalman filter", in: Proceedings. Ninth IEEE International Conference on Computer Vision 2003 vol. 1 (13–16) 2003 pp. 44–50.
- [20] A. Monnet, A. Mittal, N. Paragios, V. Ramesh. Background modeling and subtraction of dynamic scenes. in: *Proc. International Conference on Computer Vision* 2003 pp. 1305–1312.
- [21] A. Monnet, A. Mittal, N. Paragios, Visvanathan Ramesh; "Background modeling and subtraction of dynamic scenes", in: Proceedings. Ninth IEEE International Conference on Computer Vision 2003 vol. 2 (13–16) 2003 pp. 1305–1312.
- [22] A. Mittal, N. Paragios, "Motion-based background subtraction using adaptive kernel density estimation", in: Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004, CVPR 2004, vol. 2, 27 June–2 July 2004, pp. II-302–II-309.

- [23] K. Toyama, J. Krumm, B. Brumitt, B. Meyers, "Wallflower: principles and practice of background maintenance", in: *Proceedings of the Seventh IEEE International Conference on Computer Vision* vol. 1 (1999) pp. 255–261.
- [24] Y. Sheikh, O. Javed, T. Kanade, "Background Subtraction for Freely Moving Cameras", in: *IEEE 12th International Conference on Computer Vision*, 2009, Sept. 29 2009-Oct. 2 2009, pp. 1219–1225.